Available online at www.sciencedirect.com
SCIENCE DIRECT®
ACADEMIC PRESS
Journal of Environmental Economics and Management 45 (2003) 213–230
JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT
http://www.elsevier.com/locate/jeem

Valuing aboriginal artifacts: a combined revealed-stated preference approach

Peter C. Boxall,[a,*,1] Jeffrey Englin,[b] and Wiktor L. Adamowicz[c]

[a] *Canadian Forest Service, Natural Resources Canada, Canada*
[b] *Department of Applied Economics and Statistics, University of Nevada, Reno, USA*
[c] *Department of Rural Economy, University of Alberta, 515 General Services Bldg., Edmonton, Alta., Canada T6G 2H1*

Received 17 April 1998; revised 20 July 2001

Abstract

This paper examines the value of unique aboriginal cultural resources using joint revealed-stated preference methods. Our methodology exploits knowledge of previous choices from both the revealed and stated preference data to account for state dependence. We also incorporate procedures to address correlation among the data sources. The empirical application involves the discovery of aboriginal rock paintings along wilderness canoe routes in eastern Manitoba, Canada. A 4-year study of wilderness recreation trips included an SP experiment in which canoeists were asked if they would change their site choices in response to the presence of two types of rock paintings: a "pristine" painting and another spoiled by vandals. Mean welfare measures for the presence of "pristine" paintings at two canoe routes were about $61 and $77 per trip, respectively. Vandalized pictographs are worth considerably less.
© 2003 Published by Elsevier Science (USA).

1. Introduction

This paper examines the potential discovery of aboriginal rock paintings along wilderness canoe routes in the Precambrian Shield region in central Canada. The region contains about 400 paintings on rock faces along water courses [20], and some of these faces are located in popular canoeing areas (e.g. [7]). Many other areas in North America contain similar paintings or rock carvings [11]. Anthropological scholars call the paintings pictographs and the carvings petroglyphs because they represent picture writing, not necessarily works of art. These drawings were used to communicate among individuals or with the spirit world by the Aboriginal Peoples.

*Corresponding author.
E-mail address: peter.boxall@ualberta.ca (P.C. Boxall).
[1] Current address: Department of Rural Economy, University of Alberta, Edmonton, AB, Canada T6G 2H1.

0095-0696/03/$ - see front matter © 2003 Published by Elsevier Science (USA).
doi:10.1016/S0095-0696(02)00063-3

Anthropologists believe some of the pictographs in the Shield region to be 2000 years old [20]. The documentation and preservation of these sites for historical and cultural reasons is an important issue. For example, the Glen Canyon contained some spectacular petroglyphs which are now submerged beneath Lake Powell [11]. Archeological expeditions continue to discover pictographs and other artifacts in remote areas as a result of proposed hydroelectric and other developments in parts of the Canadian Shield.

Pictographs in the Shield still have spiritual and cultural significance to Aboriginal Peoples. One often observes recent offerings of tobacco, clothing, and prayer sticks nearby the paintings (pers. observ.; [7]). However, pictographs are also sought by wilderness recreationists who consider them to be an important feature of a wilderness experience [24]. Pictographs are also promoted by ecotourism operators who use them to attract clients interested in cultural experiences. The discovery of pictographs may increase visitation levels to wilderness areas, and while generating recreation and tourism benefits, may also increase the chances of vandalism.

Steinbring and Elias [21], Dewdney and Kidd [7] and others describe pictographs which have been shot at by hunters and where individuals have spray painted names or initials over them. A tension exists between making pictographs available to enjoy and the likelihood they will be vandalized. There is also concern about the importance of them to aboriginal cultures, and about the risks of vandalism. Wilderness managers should be interested in forecasting demand to view pictographs, not only to estimate their benefits, but also to provide information on the probabilities of their defacement.

This paper proceeds by developing a random utility model (RUM) that exploits revealed preference (RP) information about actual trips to existing recreation sites and stated preference (SP) information about undiscovered pictographs. A combined revealed-stated preference approach is developed that accounts for state dependence and correlation among the RP and SP data. This is followed by a description of the RP trip and site data and the SP experiment used to value the hypothetical discovery of aboriginal rock paintings along water courses in an actual wilderness area. The empirical section describes the construction of our data set. The data set combines RP information with two sets of SP data. The first SP data set focuses on a pristine pictograph while the second focuses on a defaced pictograph. The econometric model allows for the assessment of the consistency of these three data sets as well as the valuation of the pristine and defaced pictographs. The final section contains some conclusions and limitations of the analysis.

2. Theory

A variety of modeling frameworks have been proposed to analyze combined revealed and stated preference data (e.g. [1,2,6,10]). The RUM framework of Adamowicz et al. is especially appealing in settings where most individuals make a single trip, like the empirical case reported here [1,2]. In this setting the single trip nature of pure RUMs is less troubling than in other contexts [17]. The appeal of the RUM is its ability to handle substitution between sites and the direct measurement of economic welfare, while retaining the ability to test the consistency of the revealed and stated preference components of the model.

Consider a recreationist who makes a choice from a set of C possible sites. The probability (π) that site j will be visited is equal to the probability that the utility gained from visiting j is greater

than or equal to the utilities of choosing any other site in C. In this framework, it is assumed that the indirect utility function consists of the sum of two components: an observed component, V_j, and a random component ε_j. The probability of selecting site j can be written as

$$\pi(j) = \Pr\{V_j + \varepsilon_j \geq V_k + \varepsilon_k;\ \forall k \in C\}. \tag{1}$$

Empirical implementation of (1) requires the selection of a distribution to characterize the random component of the model (ε_j). McFadden [16] has shown that the choice probabilities take the following form if the random components are assumed to be independently distributed with a Type-I extreme value distribution:

$$\pi(j) = \frac{\exp(\mu V_j)}{\sum_{k \in C} \exp(\mu V_k)}, \tag{2}$$

where μ is a scale parameter. Since this parameter is not identified in a single set of data it is usually normalized to 1.

This model is typically estimated with the observable component, V_j, expressed as a linear function of m site attributes and the cost of visiting a site. A new attribute introduced into this framework will take the form of an additional attribute in the indirect utility function:

$$V_j = \sum_{1}^{m} \beta_m X_{jm} + \alpha X_{j\text{new}} + \gamma(Y_n - p_j), \tag{3}$$

where X_{jm} represents existing attributes, $X_{j\text{new}}$ represents a new attribute, Y_n is the consumer's income, p_j is the cost of visiting site j, and β, α, and γ are unknown parameters. However, by definition in the case of ex ante measurement of the new attribute, the only revealed preference data available are based on behavior that does not take into account the discovery of the new attribute. Consequently, the α parameter will be impossible to estimate. An estimable model requires situations where data exist on choices with and without the new attribute.

One alternative is to obtain a set of choice data from another location that include the new attribute and to transfer the values in a benefits transfer process. Alternatively, the ex post valuation of the attribute could be explored using revealed preference data after the discovery of the attribute. In neither case, however, can one tailor predictions of the effects of a discovery to a specific area or site. Since there is no market information about the effect of the new attribute on choice behavior, the original revealed preference data must be augmented in this situation. One way to augment the revealed preference data is to add stated preference data designed to assess the change in intended behavior resulting from the introduction of a new attribute. An analysis where revealed and stated preference information for the same set of individuals is pooled represents a potential solution to the problem.

Previous research has focused on determination of the consistency of pooled RP and SP data sets in combined models [1,2]. For a pooled set of RP and a single set of SP data this process involves the concatenation of the choice probabilities as follows:

$$\text{RP}: \quad \pi(j) = \exp(\mu_{\text{rp}} V_j) \Big/ \sum_{k \in C} \exp(\mu_{\text{rp}} V_k),$$

$$\text{SP}: \quad \pi(j) = \exp(\mu_{\text{sp}} V_j) \Big/ \sum_{k \in C} \exp(\mu_{\text{sp}} V_k). \tag{4}$$

Consistency can be tested by examining the equality of the scale parameters in the two data sets by normalizing one scale parameter and allowing the other scale parameter to vary in the estimation [22]. This method involves the notion that in any one data set μ is not identifiable, but that in any two (or more) data sets their ratio(s) can be identified (e.g. μ_{rp}/μ_{sp}).

The pooling procedure described above, however, assumes statistical independence of the revealed and stated preferences from the same individual. Some empirical research, however, has demonstrated that the revealed and stated responses may be correlated [6,15]. Thus, an empirical issue in using combined RP and SP data is accounting for potential dependence between individuals' RP and SP responses.

The issues of state dependence and correlation between RP and SP responses have not received careful examination in the valuation literature, but have received some attention in other fields. Ben-Akiva et al. [4] and Morikawa [18] suggested an approach to be used when SP responses are influenced by previous actual or revealed choices. Morikawa includes a "previous choice" term in the indirect utility function to account for state dependence and econometric modifications to account for correlation in the sequence of choices. In such an approach the correlation structure within a combined RP and SP data set may take the following form (following Morikawa):

$$\varepsilon_j^{RP} = \lambda_j + v_j^{RP},$$
$$\varepsilon_j^{SP} = \rho_j \lambda_j + v_j^{SP}. \tag{5}$$

The RP error component consists of two components which are assumed to be independently distributed noise. The first of these is a component that is "passed on" or shared with the SP error. The SP error contains an independently distributed noise component as well as a portion of the RP error (capturing the error of the previously made RP choices).

In the empirical setting described in this paper, the construction of the SP experiment involved two related questions resulting in two SP data sets (SP1 and SP2). In utilizing the pooled preference model design, we faced the issue of how to construct the error structure when more than one SP data set is pooled with RP data. A natural extension of (5) to two SP data sets would have the second set of SP choices affected by both the RP choices and the first SP choice.

While the structure in (5) accounts for correlation it does not account for state dependence. Morikawa demonstrated that "previous choice dummy variables" absorb unobserved factors relating to the preference of some alternatives over others or state dependence [18]. In the context of the RP and SP data considered in this paper, the RP choice (alternative) enters as a dummy variable in the conditional indirect utility function for the SP1 data. For the SP2 data, a dummy variable for the SP1 choice is included. These dummy variables are labeled Z_j^{RP} and Z_j^{SP1} in the equations below. Several issues arise in using dummies for state dependence. First, there is the question of whether the RP choices (dummies) should enter the SP2 utility functions or if SP1 choices (dummies) are sufficient to capture state dependence in SP2. Essentially, this questions the "lag length" to employ in the state dependence structure. As outlined in detail below, we restrict the "lag length" to be one choice, that is, only the previous choice enters the utility of the current choice.

Second, should the state dependence effects be generic or alternative specific? State dependence may be alternative specific, but in analyses with large choice sets the resulting set of previous choice variables will be intractably large. In our empirical analysis, generic state dependence

104-05984/

(previous choice in the SP1 and SP2 equations) involves a parameter constrained to be equal (δ) in the conditional indirect utility function for every alternative, as in Eq. (6) below:

$$V_j^{RP} = \sum_1^m \beta_m X_{jm} + \alpha X_{jnew} + \gamma(Y_n - p_j) + \varepsilon_j^{RP},$$

$$V_j^{SP1} = \sum_1^m \beta_m X_{jm} + \alpha X_{jnew} + \gamma(Y_n - p_j) + \delta Z_j^{RP} + \varepsilon_j^{SP1},$$

$$V_j^{SP2} = \sum_1^m \beta_m X_{jm} + \alpha X_{jnew} + \gamma(Y_n - p_j) + \delta Z_j^{SP1} + \varepsilon_j^{SP2}. \quad (6)$$

We compare this to alternative specific state dependence (Eq. (7)) which allows a test of the restriction implied by generic state dependence:

$$V_j^{RP} = \sum_1^m \beta_m X_{jm} + \alpha X_{jnew} + \gamma(Y_n - p_j) + \varepsilon_j^{RP},$$

$$V_j^{SP1} = \sum_1^m \beta_m X_{jm} + \alpha X_{jnew} + \gamma(Y_n - p_j) + \delta_j Z_j^{RP} + \varepsilon_j^{SP1},$$

$$V_j^{SP2} = \sum_1^m \beta_m X_{jm} + \alpha X_{jnew} + \gamma(Y_n - p_j) + \delta_j Z_j^{SP1} + \varepsilon_j^{SP2}. \quad (7)$$

We estimate the parameters on state dependence (δ or δ_j) as random parameters assumed to be normally distributed over the sample. This allows for the interpretation of these parameters as reflecting heterogeneity in the sample arising from different levels of experience or implicitly different "initial conditions" arising from different histories of choosing recreation sites. The initial conditions problem is pervasive in all panel data structures; thus we incorporate the random parameter approach as a way to address this issue within the context of a limited data set.

A model with alternative specific state dependence and a complex correlation structure will be difficult to estimate, especially with a relatively small data set. One can, however, simplify the model by imposing restrictions on the error structure. First, one can restrict the effect of correlation in Eq. (5) to be the same for each alternative or that the correlation between choice occasions is identical for each alternative. Second, one could impose the simplification that correlation in SP2 arises only from error in SP1, and that the RP–SP1 correlation and SP1–SP2 correlation structures are identical, yielding one correlation parameter that reflects the error structure between choice occasions (RP, SP1 and SP2). Applying these restrictions to (6) and (7) would lead to the estimation of a single parameter reflecting the correlation between choice occasions.[2] Adapting this simplified structure allows us to examine the correlation parameter ρ using techniques described in [14,23] for correlation across choice occasions. Mixed logit estimation approaches are used to identify correlation across our series of three choice occasions

[2] The structure that we employ follows the strategy suggested by Herriges and Phaneuf [14]. The structure is:

$$\varepsilon_j^{RP} = \lambda_j + v_j^{RP}, \quad \varepsilon_j^{SP} = \lambda_j + v_j^{SP},$$

where $\lambda_j \sim N(0, \sigma_\lambda^2)$ where the parameter σ_λ^2 is estimated and assumed to be positive (as it is estimated as a variance in a random parameters setting). For simplicity we call this σ_λ^2 parameter ρ.

RP, SP1 and SP2). This is not identical to the correlation structure outlined in (5), but approximates it by constructing what is essentially a panel data random effects model over the choice occasions [14].[3]

The models we estimate (Eqs. (6) and (7)) include existing attributes (X_{jm}), new attributes (X_{jnew}), prices ($Y_n - p_j$), previous choice (Z_j) and account for correlation between choice occasions (ρ). The variants of the models are: (1) a joint RP–SP model assuming $\delta_j = 0$ and $\rho = 0$, (2) a model assuming $\delta_j = \delta\ \forall j$ and $\rho = 0$, (3) a model assuming $\delta_j = \delta\ \forall j$ and an estimate of ρ, and (4) a model including estimates of δ_j and ρ. In addition, we present the revealed preference model as a base model.

Our analysis of pictographs applies this model structure to a combination of RP and multiple SP data sets, all generated from the same respondents. The next section of this paper describes these data and the potential for dependence among the RP and SP choices. The discussion then turns to consideration of the ways in which the econometric methods outlined above were implemented to estimate the various models.

2.1. The data

The study analyses wilderness recreation in Nopiming Provincial Park, Manitoba. The park is a 1440 km^2 area located about 145 km east of Winnipeg and is situated in the Precambrian or Canadian Shield (see [5]). The area contains numerous rock outcrops that can rise as much as 36 m above the surrounding countryside. These is a dominant feature and are sought by recreationists. Pictographs are frequently found on rock outcrops along watercourses in this region, and while no paintings have been reported in the park, there are some in similar areas around Nopiming and in more remote areas in [20]. The park has several river systems that contain small rapids and waterfalls that are attractive to backcountry recreationists interested in canoeing and kayaking. Most of the park is forested. Jack pine is the most abundant tree species in the park, although considerable areas of black spruce, aspen and white spruce can be found.

The wilderness recreation in this park and the surrounding region has been carefully studied in recent years. This involved an economic assessment of the importance of fire, forest ecosystems and other features [5,8]. As a result there is a detailed inventory of features along canoe routes that was verified through intensive field work and GIS databases provided by Manitoba Natural Resources. The field work identified two specific routes in Nopiming that had the potential to have rock paintings.

A registration system was developed to provide an understanding of the frequency of visitation to the backcountry areas of the park. In 1995 the registrants were surveyed. The survey included a stated preference experiment in which backcountry visitors were asked to respond to the possible presence or discovery of rock paintings in the park. The survey sample was created using the names of the leaders of the recreation parties who registered for a backcountry trip in Nopiming Park in 1993 or 1994. The original sample of 661 registrants was reduced to 587 by eliminating

[3] Correlation across choice occasions is examined by specifying an element of the random component that does not vary over time or over RP, SP1 and SP2 choices. If the parameter on this component is specified as a random parameter with mean zero and an estimated variance, then the variance becomes an estimate of the covariance between RP, SP1 and SP2 choices or correlation between unobserved RP, SP1 and SP2 error elements [14].

incomplete addresses, and multiple trips by the same individual. There were, however, very few recreationists who took more than one trip in a year. The final sample included individuals from five Canadian provinces, and three American states.

The experiment involved presenting pictures of two actual pictographs to respondents. The first involved a "pristine" pictograph which exists in a more remote wilderness area in Ontario northeast of Nopiming. The second involved a picture of a pictograph located in a remote area in northern Manitoba that had been defaced by vandals and also appears to be weathered. These pictures were taken by Peter Boxall and David Watson during trips to the area in 1994. These pictures and the stated preference questions used in the experiment are shown in Fig. 1.

The survey design exploited the knowledge of historical trip behavior. Each respondent was offered the chance to change their trip to another route to see a rock painting. Since the original trip was known, each respondent was offered the rock paintings at a site they had not visited during the study period (1991–1994). Thus, the experiment ensured that every respondent had an opportunity to change their original site choice to a different site. The pictographs were offered at

Suppose that a (rock painting) looking like **photograph E** was located on the Manigotagan River route. Would you have visited this route **instead of the actual route you visited on your first trip to Nopiming in 1993 or 1994?**

YES _____ NO _____

If your answer was yes above, would you still have changed your trip to the Manigotagan River route if the rock painting looked like **photograph F** below?

YES _____ NO _____

Photograph E

Photograph F

Fig. 1. The photographs and representative questions used to generate the two stated preference data sets used in the analysis.

two routes: the Seagrim Lake canoe route and the Manigotagan River route. These sites were chosen because they were the only routes in the park that had rock outcrops similar to those areas where pictographs are typically found. Note that an orthogonal design would be inappropriate here. If pictographs were offered on other routes (besides Seagrim or Manigotagan) it would imply rock outcrops that do not exist at those sites. Since most of our respondents are quite knowledgeable about the area, offering pictographs at other sites would confound our efforts to value pictographs by changing other site characteristics. Respondents were first asked if they would change their choice given the presence of a "pristine" pictograph. They were subsequently asked if they would continue to choose this site if the pictograph was defaced.

The survey included a total of three mailouts. First, a questionnaire and cover letter was sent to the 587 individuals in early March 1995. Two weeks later a reminder post card was sent to any individual who had not responded. Finally, 5 weeks after the original mailout, a second questionnaire and cover letter was sent to nonrespondents. These procedures resulted in the return of 431 completed questionnaires which, adjusting for undeliverables (e.g. people moving etc.), represented a response rate of 81%.

The final data sets used for analysis consist of actual site choices for the respondents for 1993 and 1994 (RP data) and their stated choices from the questionnaire (SP data). In this information, the choice set was limited to the eight major routes in the park. Any respondent whose actual trips were not to any of these eight routes was excluded from the analysis. This resulted in a final sample consisting of 386 respondents with complete trip and questionnaire data. Boxall et al. identified 14 route attributes that explained the choice of a canoe route in the same park [5]. These included travel costs, the incidence of historical fires, the amounts of various forest ecosystems, indicators of the level of physical effort required to complete the route, and some alternative specific constants. All of these variables and various combinations were initially examined as explanators of site choice, but only travel costs and three others (not including pictographs) could be identified in this study. The Boxall et al. study, however, used 20 routes in the analysis, of which eight were the same as those in the present study. Thus, the reduced number of routes suggests that only a subset of the full set of the independent variables used previously may be significant explanators of site choice.

2.2. *The econometric model*

In the RP data and each set of SP data the eight routes form the choice set, and four independent variables comprise the route characteristics (X_{RP}). Since there are two types of pictographs, one dummy variable was created for each type. The first involved the pristine pictograph (α_1) which has a value of 1 at the route it was presented to the respondent in the questionnaire (Seagrim or Manigotagan) and a value of 0 otherwise. The defaced pictograph variable (α_2) was similarly constructed. There was no pictograph present in the RP choice data so both pictograph variables had values of 0 at each of the 8 routes.

As described above, the construction of the SP experiment (Fig. 1) involved two related questions. The first asked a respondent if they would switch their original trip to a different route given the presence of a pristine pictograph. The second question asked, *conditional on switching their trip in the first SP question*, if they would still switch if the pictograph was vandalized. To address the state dependence which arises among these data sets, previous choice vectors were used

when pooling the data sets. In our case the RP choice vector from each individual was added to their SP1 information. Since the second SP question was contingent on the first SP question (and not the RP choices) the choice vector from the SP1 data was added to the SP2 observations. Following the framework shown in Eq. (6), the parameters on these previous choice vectors were constrained to be the same. However, in utilizing the framework implied by Eq. (7), the constrained δ was "modified" by including terms which represent the previous choice interacted with or multiplied by alternative specific constants (ASCs) or dummy variables. This procedure allows capture of alternative specific state dependence (δ_j). In order to explore heterogeneity in the data, both conventional and mixed logit procedures were used to estimate the δ and ρ parameters.

As discussed above we utilized Herriges and Phaneuf's mixed logit approach to incorporate correlation [14]. This involved including ASCs in the pooled data, specifying the parameters of the ASCs to be random with means equal to 0 and variances constrained to be equal across the three data sets. The resultant constrained variance parameter of the ASCs represents ρ.

The log likelihood function for the joint models incorporating generic state dependence and correlation among the data elements in our problem for the sample of N individuals, is given by

$$\mathrm{LL} = \sum_{n=1}^{N(\mathrm{RP})} \sum_{K \in C} \ln \pi_n\{j|\gamma, \beta, \delta, \rho\} + \sum_{n=1}^{N(\mathrm{SP1})} \sum_{K \in C} \ln \pi_n\{j|\gamma, \beta, \alpha_1, \delta, \rho, \mu_{\mathrm{sp1}}\} + \sum_{n=1}^{N(\mathrm{SP2})} \sum_{K \in C} \ln \pi_n\{j|\gamma, \beta, \alpha_2, \delta, \rho, \mu_{\mathrm{sp2}}\},$$

where γ is the parameter on travel costs, β represents the parameter vector on the site attributes, α_1 and α_2 represent the dummies on the two pictograph variables, μ_{sp1} and μ_{sp2} are the relative scale parameters on the two SP data sets (with the RP scale as the base), δ represents the aggregate or stacked previous choice vector consisting of a vector of zeros for the RP information, the choice vector from the RP data, and SP1 choice vector from the pristine pictograph set of SP data and ρ represents the correlation term. The first part of the log likelihood function corresponds to the RP data and the second two components correspond to the two SP data sets. Note that β, δ, as well as ρ, are constrained to be equal across the three data sets, while the pictograph variables (α_1 and α_2) are estimated independently. As noted above, the models presented below include generic estimates of δ as well as alternative specific estimates of δ_j. In the models reported below, μ_{sp1} and μ_{sp2} were set equal to 1.0.

The econometric analysis involved estimating conditional logit models and mixed logit models in which the state dependence and correlation parameters were specified as random, normally distributed variables. For the mixed logit estimations Ken Train's simulated maximum likelihood program (http://elsa.berkeley.edu/~train) was used with 100 Halton draws.

3. Results

The actual site choices of the respondents and their response to the SP experiment is shown in Table 1. About 42% of the respondents in the sample indicated they would change their actual route choice to another route to view a pristine painting. This change would occur regardless of the route where a painting was discovered (Seagrim and Manigotagan). However, only about

Table 1
Actual and hypothetical site choices in response to aboriginal pictographs by wilderness recreationists at Nopiming Provincial Park, Manitoba

Canoe routes	Original number of trips	Number of surveys where pictographs were offered	Number of people switching for a pristine pictograph	Number of people switching for a vandalised pictograph
Tulabi	183			
Shoe	12			
Rabbit	58			
Seagrim	41	246	103	28
Gem	12			
Beresford	40			
Manigotagan 1	19	140	58	14
Manigotagan 2	21			
Total	386	386	161	42

10% of the respondents would change their behavior to view a defaced painting. The effect of the pictograph attributes on site choice is portrayed in Fig. 2 where the cumulative increase in the number of trips to Seagrim and Manigotagan is shown relative to the availability of the two types of paintings.

Tables 2 and 3 show the parameters for seven econometric models (Table 3 contains the estimates of the previous choice parameters for models 3–7). The second column in the table reports results for a model estimated with only the RP observations. Note that the utility function includes travel costs,[4] three forest characteristics variables, and one ASC which represents two routes which incorporate rapids or white water sections along the Manigotagan River. The third column shows parameters for a conditional logit model estimated with data pooled over the three sets of data. This model includes the pictograph parameters. The last five columns present results from models using the pooled or joint RP–SP data which have various specifications in terms of the impact of the previous choice and the extent of correlation across the RP and SP decisions.

In all of the models the parameters on travel costs to the route, hectares of recent burned areas, and hectares of black spruce old growth ecosystems are negative; but are positive on hectares of white spruce growth and the single ASC. All of these parameters are statistically significant. These results are consistent with previous research on site choice behavior in the park involving a larger set of canoe routes [5], and with trip data from different years (1991 and 1992) using a smaller set of routes [8].

In the RP model there is no parameter for pictographs because they are not available. However, pictograph parameters are estimated in the joint models. These parameters are positive for both

[4]Travel costs were estimated using the standard approach in the literature (e.g. [9]). This involves two calculations: (i) the out-of-pocket expenses estimated as $0.25 (the round trip distance in kilometers) and (ii) the opportunity cost of time estimated as one-quarter of a respondent's annual income divided by 2080 h multiplied by the travel time. Travel time was estimated using an average speed of 90 km/h during the round trip distance.

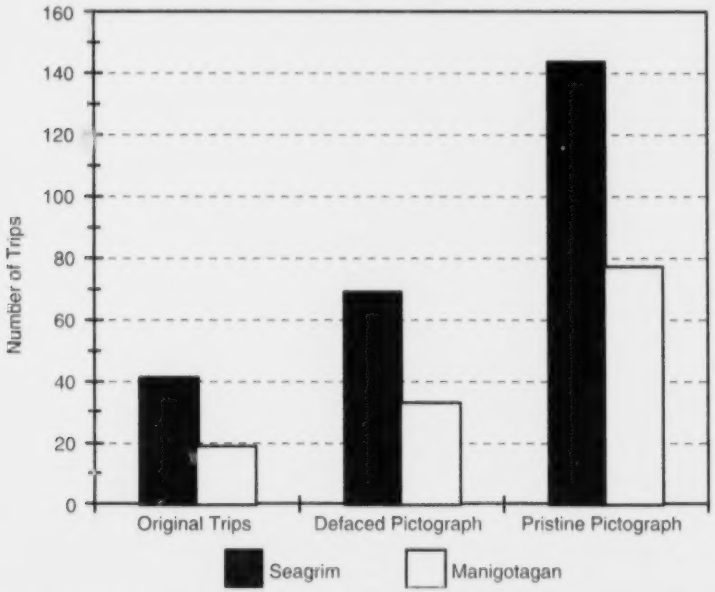

Fig. 2. The frequency distribution of trips with and without pictographs at two canoe routes in Nopiming Provincial Park, Manitoba.

the pristine and defaced pictograph in the one joint model (model 2) that does not incorporate potential dependence among the pooled data in the error term. The SP choices may be negatively correlated with the RP or previous choice because the number of respondents who agreed to switch routes to see the pristine painting was high (Table 1). In addition, because of the structure of the SP experiment, the second SP choice may be correlated with the first SP choice. These issues are addressed in the remaining joint models (models 4–7, Table 2) where there is sufficient variation to identify the pictograph variables as well as state dependence and correlation.

In models 3–5 the generic previous choice variable, δ, has a significant positive coefficient, indicating dependence of choices among the three data sets (Table 3). In models 4 and 5 where generic state dependence is specified as a random variable, the mean of δ is larger and most of the other utility function parameters are similar to the RP and the simple joint model (model 2).[5] However, including the generic previous choice parameter in the estimation has significant impact on the pictograph variables. The pristine pictograph parameter becomes much larger, while the defaced pictograph parameter changes from a small positive value to a larger negative one. Specifying δ as random serves to increase the magnitudes of these parameters. Accounting for state dependence among choices in our three data sets has considerable impact on the parameters of interest, and therefore the welfare measures associated with the two types of pictographs. On

[5]This increased size of δ arises from the fact that the variance of the estimator is reduced (by explaining more variation through random parameters), and since the coefficient estimates are implicitly the ratio of the parameter over variance, the size of the parameter estimate increases.

Table 2
Parameters (standard errors) of the Indirect Utility Function

Variables	Revealed preference model	Joint model	Joint model with generic state dependence		Joint model with generic state dependence and correlation	Joint with alternative specific state dependence	Joint with alternative specific state dependence and correlation
	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)	(Model 7)
Travel cost	−0.0682*	−0.0633*	−0.0501*	−0.0541*	−0.0542*	−0.0530*	−0.0530*
	(0.0058)	(0.0032)	(0.0049)	(0.0053)	(0.0053)	(0.0055)	(0.0055)
Burn	−0.2005*	−0.1675*	−0.1514*	−0.1661*	−0.1661*	−0.1742*	−0.1742*
	(0.0190)	(0.0120)	(0.0157)	(0.0169)	(0.0169)	(0.0173)	(0.0173)
Black spruce	−1.2464*	−0.9896*	−0.8416*	−0.9263*	−0.9265*	−0.9468*	−0.9470*
	(0.1187)	(0.0680)	(0.0949)	(0.1042)	(0.1042)	(0.1043)	(0.1043)
White spruce	5.4570*	4.4315*	3.6616*	4.0133*	4.0140*	4.0252*	4.0258*
	(0.6321)	(0.3823)	(0.5108)	(0.5494)	(0.5495)	(0.5628)	(0.5628)
Pristine Pictograph (α_1)		2.2368*	6.1721*	7.2693*	7.2704*	6.4282*	6.4307*
		(0.1184)	(0.3791)	(0.6008)	(0.6009)	(0.5632)	(0.5637)
Defaced Pictograph (α_2)		0.4440*	−4.2224*	−5.9421*	−5.9440*	−4.5355*	−4.5383*
		(0.1731)	(0.4056)	(0.7951)	(0.7954)	(0.6815)	(0.6830)
Manigotagan Route (ASC)	2.6138*	2.4959*	1.8011*	1.8543*	1.8546*	1.7299*	1.7302*
	(0.3652)	(0.2016)	(0.3036)	(0.3252)	(0.3252)	(0.3446)	(0.3447)
Log L	−673.35	−2045.16	−1317.34	−1309.06	−1309.05	−1297.95	−1297.9

*Indicates significant at the 95% level or beyond.

Table 3
Parameters (standard errors) of the error structure associated with the models presented in Table 2

Error terms	Model 3	Model 4	Model 5	Model 6	Model 7
δ (prev. choice)	5.6667*	6.8879*	6.8893*	6.8473*	6.8491*
	(0.3590)	(0.6152)	(0.6154)	(0.5637)	(0.5644)
SD (δ)		2.2329*	2.2344*	0.9196	0.9264
		(0.4822)	(0.4823)	(0.9744)	(0.9746)
δ1				−1.4258*	−1.4245*
				(0.4706)	(0.4700)
SD (δ1)				0.1020	0.0987
				(1.0608)	(1.0520)
δ2				−0.2038	−0.2019
				(0.9320)	(0.9292)
SD (δ2)				0.2879	0.2823
				(3.8190)	(3.6320)
δ3				−0.5879	−0.5838
				(0.7434)	(0.7434)
SD (δ3)				0.1550	0.1665
				(1.6292)	(1.6218)
δ4				−1.3640*	−1.3638*
				(0.4437)	(0.4437)
SD (δ4)				0.4077	0.4021
				(1.5797)	(1.5844)
δ5				0.8348	0.8346
				(0.9017)	(0.9000)
SD (δ5)				0.4965	0.4887
				(3.6429)	(3.6231)
δ6				−1.1863*	−1.1842*
				(0.6091)	(0.6088)
SD (δ6)				0.1815	0.1800
				(1.0863)	(1.0900)
ρ			0.0202		0.0254
			(0.1626)		(0.1612)

*Indicates significant at the 95% level or beyond.

the other hand, correlation does not appear to be an issue with these data since in model 5 ρ is insignificant and its inclusion has virtually no effect on the other parameters of interest. No additional correlation is discovered once the correlations from previous choices are captured through our state dependence specification.[6]

In model 6 we further examine state dependence through estimating random alternative specific estimates of δ_j and in model 7 we incorporate correlation (see Table 3). We could not estimate the full set of δ_j in either model, probably because we incorporated an ASC in the utility function for the two routes (routes 7 and 8 represent the Manigotagan ASC). We address this by estimating δ and six δ_j parameters. Thus, the "true" δ_j for the six routes represent modifications of δ (i.e. $\delta - \delta_j$) and alternative specific state dependence for the two remaining routes is captured by δ minus the sum of the six δ_j reported in Table 2. In the pooled data the state dependence effect is significant for alternatives 1, 4 and 6 and insignificant for the remainder. Note that in model 7 the correlation parameter is insignificant. Likelihood ratio tests show that model 6 dominates models 3–5. We conclude that the introduction of a random specification of state dependence, as well as incorporating its alternative specific effects, is empirically important and in our data, results in a superior model.

A final issue is the question of scaling of the three data sets. The data were unable to support the full information maximum likelihood estimation of the effects of correlation, state dependence and scaling. Nevertheless, scaling was explored in simpler models to develop some intuition for their importance empirically. The log likelihood values for the two single SP models, ignoring dependence among the data sets, were −641.3 for the pristine pictograph model and −716.7 for the defaced pictograph model. A likelihood ratio test of the fit of the combined versus the three free models was not significantly different at the 5% level ($\chi^2 = 12.6$, 14 df) suggesting that $\mu_{sp1} = \mu_{sp2} = 1$. For the related joint model that considers the correlation as a random parameter (model 4), the same log likelihood ratio test suggests that this joint model appears to not satisfy the condition of parameter equality when $\mu_{sp1} = \mu_{sp2} = 1$ ($\chi^2 = 61.92$ which is not close to the critical value of 26.3 at 16 df). We have not conducted the same test with rescaling of the stated preference information (i.e. when μ_{sp1} and μ_{sp2} are allowed to vary in the estimation procedure). However, comparison of the RP model parameters with those of the joint model with correlation suggest that differences between them are not large. Models that incorporate correlation, state dependence and scaling simultaneously could not be estimated successfully with these data. Models addressing all these components would be desirable in future studies if those data can support such a rich empirical structure.

Since correlation was found to be insignificant (subject to the caveat in footnote 5) and state dependence important, we use the parameters from model 6 to assess the welfare effects of discovering pictographs at the two routes in the park. Although RP and SP data are used to estimate the parameters, we assume that a single indirect utility function underlies all choices. State dependence generated by our experimental procedure is not directly represented in the

[6]This interpretation should be treated with caution since our estimate of correlation is insignificant in the presence of previous choice parameters. It may be the case that the correlation exists but is captured by including previous choices in the model. Furthermore, the approach to modeling the error correlation may be muting the effect of serial correlation. Given the restrictions and specification, further evidence of serial correlation does not appear in our estimates.

welfare calculation because it is part of the econometric error structure, not the indirect utility function. As a result we have an ex ante indirect utility function on which we base our welfare analysis.

Using Hanemann's formula [12]. For the pristine pictograph case, this welfare measure is straightforward and is represented by

$$CV = \frac{1}{\gamma}\left[\ln\left(\sum_{1}^{8} \exp^{V\beta}\right) - \ln\left(\sum_{1}^{7} \exp^{V\beta} + \exp^{V_s\beta+\alpha_1}\right)\right], \tag{8}$$

where the last term includes the pictograph variable at one of the eight sites. However, for the vandalized pictograph case the definition of the base situation is more complex. Since the choice of the site with the vandalized painting was contingent on choosing the site where the pristine one was located, the base must be the situation with the pristine pictograph. In other words, the welfare measure must reflect a change in quality of the pristine pictograph. This is captured in the welfare calculation as the difference between the pictograph parameters, α_1 and α_2:

$$CV = \frac{1}{\gamma}\left[\ln\left(\sum_{1}^{7} \exp^{V\beta} + \exp^{V_s\beta+\alpha_1}\right) - \ln\left(\sum_{1}^{7} \exp^{V\beta} + \exp^{V_s\beta+\alpha_1-\alpha_2}\right)\right]. \tag{9}$$

Since the welfare measures we report are the first for pictographs in the literature, we also provide estimates of the variance of the welfare measures using the simulation technique developed by Park et al. [19].

The change in site choice behavior as a result of the presence of pristine pictographs increases the benefits of a canoe trip to the park. This mean increase is $77.26 per trip (SD = 13.94) if the pictograph was located at the Seagrim route and $61.31 per trip (SD = 11.31) if it was located on the Manigotagan route. To put these values in context, the value of a canoeing trip to Nopiming Park in 1993–94 was about $293 [9]. Pictographs, if discovered, would significantly affect the pattern of trips to this park and considerably enhance welfare. The mean benefit, however, would fall to $8.39 (SD = 3.47) and $3.96 (SD = 1.64) per trip if the painting was subsequently vandalized. Thus, at these routes, a recreationist "endowed" with a pristine pictograph would experience a significant loss if this painting was vandalized.

4. Discussion

One important challenge facing managers of public lands is the tension between use, overuse and risk of damage to the site attributes. Clear cases in point are cultural resources such as the pictographs studied in this paper. In this analysis the value of pictographs to wilderness recreationists is examined. Pristine pictographs are quite valuable, in some cases as much as $77.00 per trip, a value that compares favorably with the costs of accessing remote cultural sites. A discovered pictograph that is subsequently defaced, however, is worth about 6–10% of the value of the painting in its pristine state. This difference in values between vandalized and undefiled attributes is frequently speculated in the literature [13], and is empirically verified in our study. The contrast in values suggests that concerns over the effect of vandalism on tourism or recreational experiences are well founded. Of course, knowing the values of pictographs does not

solve the management challenge associated with their presence. There remains the question of whether it is worthwhile forgoing the benefits associated with the pristine pictograph to reduce the risk of the pictograph being vandalized. Knowledge of the risk of vandalism is also needed to conduct a rational policy discussion of this issue. However, without estimates of values, no economic discussion of the merits of different policies can be conducted.

An additional problem faced by public land managers concerned with areas currently used by indigenous peoples is the protection of spiritual and cultural artifacts. In Canada information about the location of these features is collected at times from Aboriginal Peoples, but is frequently not released to the public for fear of depreciative behavior on the part of non-Aboriginal Peoples. The approach used in this paper to examine switching behavior of recreationists in response to discoveries of pictographs would allow the forecasting of visitation levels. Managers could use these forecasts to design access plans or other policies to reduce the chances of discovery of places of significance to Aboriginal Peoples, and thus decrease the probabilities of vandalism or other depreciative behaviors.

This paper also makes a contribution to the use of combined RP and SP data in nonmarket valuation research. Early work joining stated and revealed preference data in random utility models struggled to develop methods that tested the consistency of the behavior suggested by revealed and stated data. Quite often the two data sets were not consistent with one another unless one was scaled [1,3]. In our analysis of three data sets, we first addressed state dependence using Morikawa's suggestion to include the previous choice as an explanator of stated choices [18]. We defined this state dependence parameter as a component of the error term of the choice model and specified it as random normally distributed parameter to account for heterogeneity among our respondents. We also examined the effect of state dependence in an alternative specific manner. State dependence was found to have a significant influence in our combined RP–SP data. In addition, we examined correlation between choice occasions in our combined data using the approach suggested by Herriges and Phaneuf [14] and Train [23]. In our case, once state dependence was included in the model, this correlation was not found to arise in the choice behavior of our respondents.

The way in which previous choices can account for correlation among RP and SP data is highly dependent on the SP experiment employed. In the SP experiment examined in this study, we were interested in the discovery of an artifact and its subsequent defacement. Thus, there was good reason to believe that the first SP question was related to the RP choices, and that the second SP question was related to the choice in the first SP question. The construction of the state dependence terms involved combining the RP choices and the first SP choices to account for this structure in the joint estimation of parameters. However, if we had asked respondents if they would have switched their *original* trip to view a pristine pictograph, and if they would have switched their *original* trip to view a defaced one, the structure would be different. In this latter case, the previous choice variable for each of the SP questions would be the RP choices. Note that this particular analysis could be used to compare, independently, the values of a pristine pictograph with a vandalized one. This approach could not be used to examine the change in the value of a discovered pristine pictograph that is subsequently vandalized.

Pictographs are well known to Canadians who live in the study region and these artifacts are well known to those who visit wilderness areas there. This study was undertaken as part of a

larger effort focused on modeling wilderness site choice behavior in the Canadian Shield region. In this larger context the role of landscape features, ecosystem processes such as forest fires, and wilderness managerial features were understood. This knowledge helped to clarify the existing processes that are driving the choices of wilderness canoeists in the region and allowed us to examine the incorporation of new attributes such as pictographs in these choice processes. Furthermore, the detailed past information base about the recreationists allowed the survey used in this study to be "custom designed" for each respondent. This design, in concert with the significant amount of previous research in this geographic area likely enhanced the modeling efforts reported in this paper.

This paper raises a number of questions. For example, an important issue is the possibility of the model over-predicting switching behavior. Ben-Akiva and Morikawa found this feature in their analysis of travel modes using a similar combined estimation approach [3]. Furthermore, it is unclear whether the switching of routes would continue to occur in the long run. It is possible that dynamic forces may play a role in site choice behavior with discoveries causing switching once or twice, but not permanently. An additional issue is the effect of discoveries on the levels of visitation. In the empirical example examined in this paper, very few individuals actually took more than one trip a year. Related research on these recreationists suggests that trip quantities do not vary significantly with changes in route qualities [8]. There is no reason to believe that the presence of pictographs would change this behavior in a significant manner. Nevertheless, this issue and the questions of dynamic behavior raised above represent worthy topics for future research in this area.

The objective of this paper was to improve understanding of the demand by recreationists for aboriginal artifacts in wilderness areas. The approach used to examine this issue was to analyze combined revealed and stated preference data. The results suggest that wilderness users would switch their site choices to areas with artifacts and that this would generate large recreation benefits. However, with increased levels of visitation comes an increased risk of vandalism which, in turn, affects the generation of benefits to recreationists and Aboriginal Peoples. The successful management of wilderness areas containing aboriginal artifacts will require the development of extensive and reliable databases. The effectiveness of the stated preference design used in this study was only possible due to high levels of understanding of the users of the wilderness areas.

Acknowledgments

We thank Joe Herriges and two anonymous reviewers for substantial comments on this paper. We gratefully acknowledge David Watson for creative field work in the Shield country and for assisting with the survey design and administration. Kent Baylis, Dan Benoit, Jennifer Lidgett and Janet Lutz also provided valuable field assistance. This research was funded by the Canada-Manitoba Partnership Agreement in Forestry and the Socioeconomic Research Network of the Canadian Forest Service.

References

[1] W.L. Adamowicz, J. Louviere, M. Williams, Combining stated and revealed preference methods for valuing environmental amenities, J. Environ. Econom. Management 26 (1994) 271–296.
[2] W.L. Adamowicz, J. Swait, P.C. Boxall, J. Louviere, M. Williams, Perceptions versus objective measures of environmental quality in combined revealed and stated preference models of environmental valuation, J. Environ. Econom. Management 32 (1997) 65–84.
[3] M. Ben-Akiva, T. Morikawa, Estimation of switching models from revealed preferences and stated intentions, Transport. Res. 24A (1990) 485–495.
[4] M. Ben-Akiva, T. Morikawa, F. Shiroishi, Analysis of the reliability of preference ranking data, J. Bus. Res. 24 (1992) 149–164.
[5] P.C. Boxall, D.O. Watson, J. Englin, Backcountry recreationists' valuation of forest and park management features in wilderness parks of the western Canadian Shield, Canad. J. For. Res. 26 (1996) 982–990.
[6] T.A. Cameron, Combining contingent valuation and travel cost data for the valuation of nonmarket goods, Land Econom. 68 (1992) 302–317.
[7] S. Dewdney, K. Kidd, Indian Rock Paintings of the Great Lakes, University of Toronto Press, Toronto, ON, 1962.
[8] J. Englin, P.C. Boxall, K. Chakraborty, D.O. Watson, Valuing the impacts of forest fires on backcountry forest recreation, For. Sci. 42 (1996) 450–455.
[9] J. Englin, P.C. Boxall, D.O. Watson, Modeling recreation demand in a Poisson system of equations: an analysis of the impact of international exchange rates, Amer. J. Agric. Econom. 80 (1998) 255–263.
[10] J. Englin, T.A. Cameron, Augmenting travel cost models with contingent behavior data, Environ. Res. Econom. 7 (1996) 133–140.
[11] C. Grant, The Rock Art of the North American Indians, Cambridge University Press, Cambridge, 1983.
[12] W.M. Hanemann, Applied welfare analysis with qualitative response models, Working Paper No. 241, Univ. California, Berkeley, CA, 1982.
[13] A. Harrison, Problems: vandalism and depreciative behavior, in: G.W. Sharpe (Ed.), Interpreting the Environment, Wiley, New York, NY, 1976.
[14] J.A. Herriges, D.J. Phaneuf, Inducing patterns of correlation and substitution in repeated logit models of recreation demand, Amer. J. Agric. Econom. (2002) 1076–1090.
[15] J.-C. Huang, T.C. Haab, J.C. Whitehead, Willingness to pay for quality improvements: should revealed and stated preference data be combined?, J. Environ. Econom. Management 34 (1997) 240–255.
[16] D. McFadden, Conditional logit analysis of qualitative choice behavior, in: P. Zarembka (Ed.), Frontiers in Econometrics, Academic Press, New York, NY, 1973.
[17] E.R. Morey, What is consumer surplus per day of use, when it is a constant independent of the number of days of use, and what does it tell us about consumer surplus?, J. Environ. Econom. Management 26 (1994) 240–255.
[18] T. Morikawa, Correcting state dependence and serial correlation in the RP/SP combined estimation method, Transportation 21 (1994) 153–165.
[19] T. Park, J.B. Loomis, M. Creel, Confidence intervals for evaluating benefit estimates from dichotomous choice contingent valuation studies, Land Econom. 67 (1991) 64–73.
[20] G. Rajnovich, Reading Rock Art: Interpreting the Indian Rock Paintings of the Canadian Shield, Natural Heritage/Natural History Inc., Toronto, ON, 1994.
[21] J. Steinbring, D. Elias, A key pictograph from the Bloodvein River, Manitoba, Amer. Antiquity 33 (1968) 499–501.
[22] J.R. Swait, J.J. Louviere, The role of the scale parameter in the estimation and comparison of multinomial logit models, J. Marketing Res. 30 (1993) 305–314.
[23] K.E. Train, Mixed logit models for recreation demand, in: C. Kling, J. Herriges (Eds.), Valuing the Environment using Recreation Demand Models, Edward Elgar, Lyme New Hampshire, 1997.
[24] D.O. Watson, P.C. Boxall, B.L. McFarlane, Characteristics and management preferences of wilderness users in eastern Manitoba, Canadian Forest Service, unpublished report, 1998.